Automating Headpose-Based Trial Selection in Infant EEG Using Convolutional Neural Networks

Max Schulz [1,3], Robin Nehler [2,3], Malte Wöstmann[1,3] & Sarah Jessen[2,3]

1 Department of Psychology, University of Lübeck, Germany
2 Institute of Medical Psychology, University of Lübeck, Germany
3 Center of Brain, Behavior and Metabolism (CBBM), Lübeck, Germany

max.schulz@uni-luebeck.de | robin.nehler@uni-luebeck.de

BABYLAB
Universität zu Lübeck

Background & Theory

Inattention and fussiness [1] are a common problem in infant research. A major issue occurs when infants look away from visual stimuli, leading to trials that **lack meaningful engagement**.

Traditional video-based coding of attention is slow, subjective, and prone to inter-rater variability. Additionally, exclusion of trials due to a dichotomous criterion can be overly restrictive, therefore inviting new innovate approaches to process data [2]. To address this, we developed **OCAPI** (**O**bjective **C**oding of **A**ttention **P**ipeline for **I**nfants),an **automated, objective pipeline** [3,4] **that uses synchronised video and EEG event markers** and adds several metrics, not just a binary in/out .

OCAPI defines each infant's baseline gaze and head pose via **density-based spatial clustering**. For every trial, a **convolutional neural network extracts facial landmarks** to estimate **gaze direction** and **head pose**. Trials are continuously weighted or can be labelled on-target when coordinates fall within the baseline region and off-target when they exceed a defined threshold.

This approach provides a clear, **reproducible standard** for increasing statistical power or possibly removing whole trials, removes subjective judgement, and improves efficiency. This offers a reliable and transparent framework for enhancing data quality in infant EEG research.

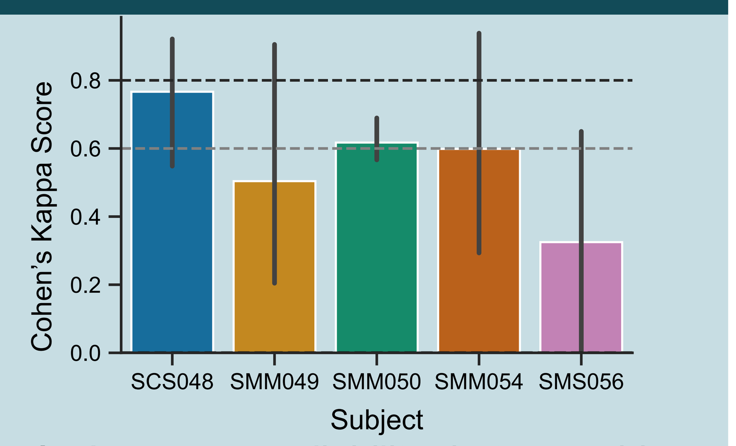
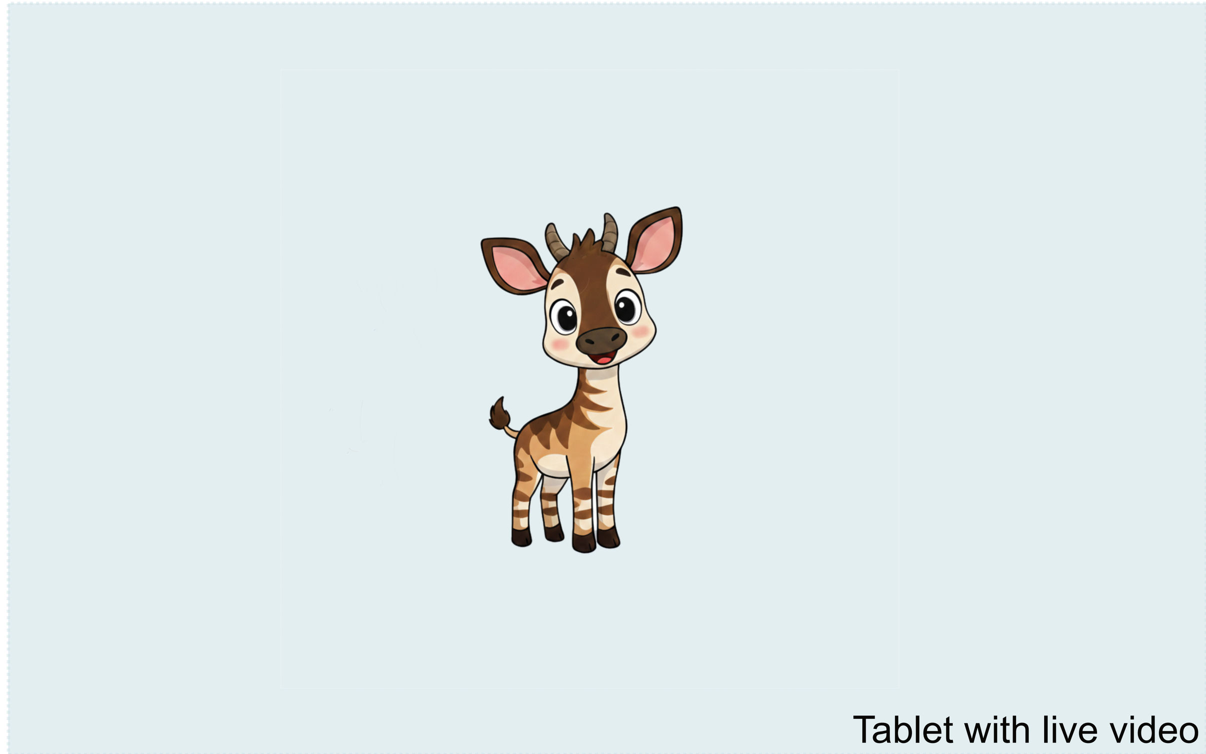


Fig. 1: Inter-rater reliability between binary sequences of two human raters on three sessions of five infant subjects, respectively. Error bars represent 1 s.e.m.

Results

Fig. 2: OCAPI components. **A:** A CNN (MediaPipe [4]) detects facial landmarks for subsequent head pose and gaze estimation[3]. **B:** Based on a region of interest and synchronized with event timings, trial onsets are registered. **C:** A density-based spatial clustering algorithm detects baseline head pose and gaze.



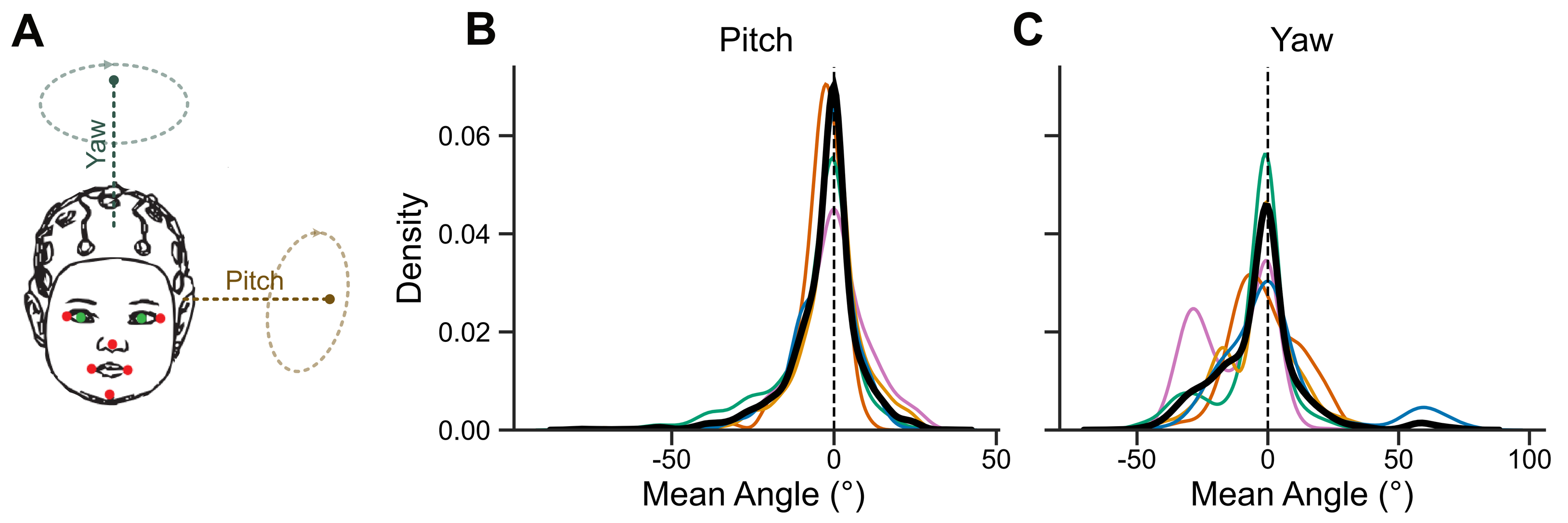


Fig. 3: A: Pitch (vertical axis) and Yaw (lateral axis) illustrated. **B:** Distribution of mean head angles per trial of pitch **C:** and yaw plotted for each infant (5 infants with 3 sessions each), allowing to estimate quality of looking behavior and separate inter-individual movement differences. Each colored line represents one subject.

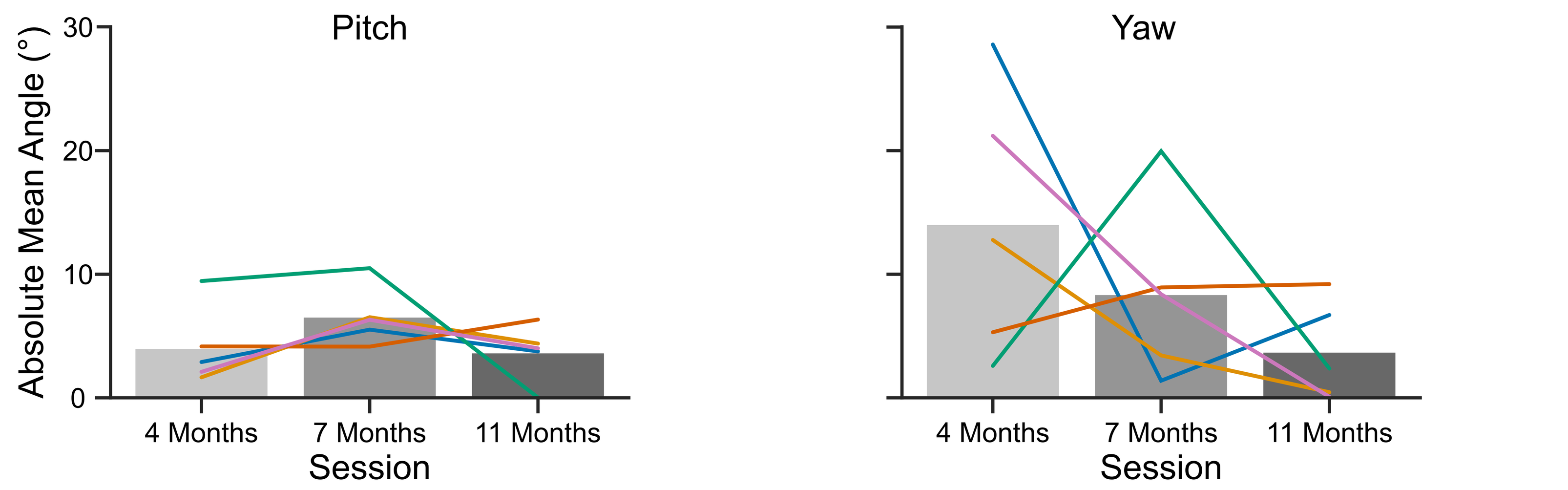


Fig. 5: Absolute head pose deviation from baseline by session. A mean angle of 0° would be perfect baseline-alignment. Each colored line represents one subject.

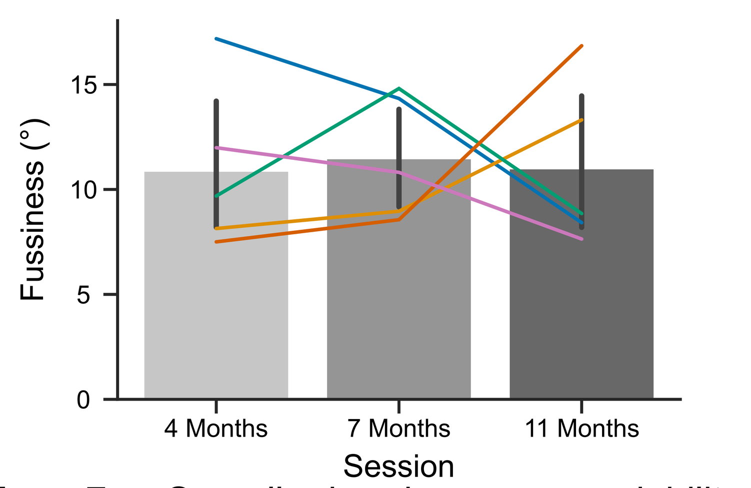


Fig. 7: Overall head pose variability (fussiness) across sessions. Variability shown here is defined as one standard deviation away from the subject mean. Each colored line represents one subject.

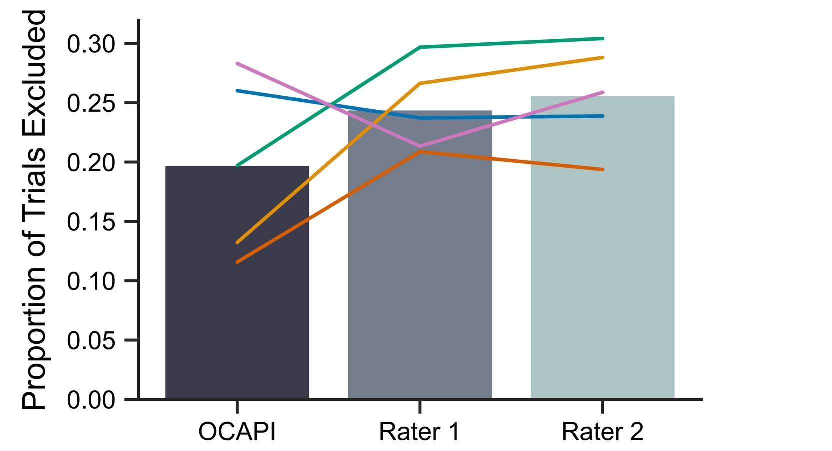


Fig. 8: Mean excluded trials per coding instance. On average, OCAPI removes fewer trials compared to human evaluations. Each colored line represents one subject.

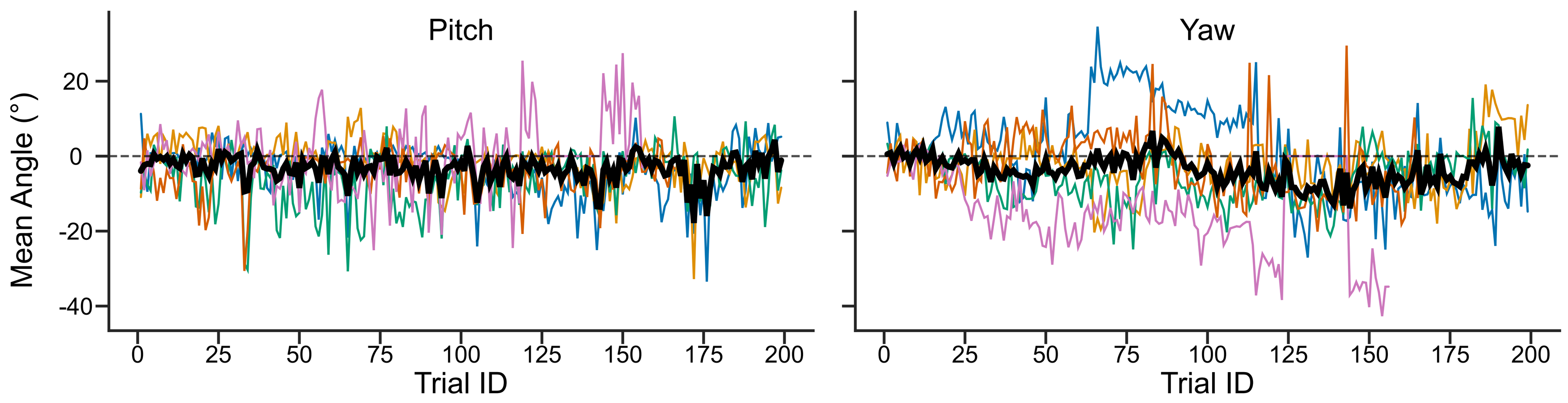


Fig. 4: Mean head pose as a function of Trial ID. Each colored line represents one subject.

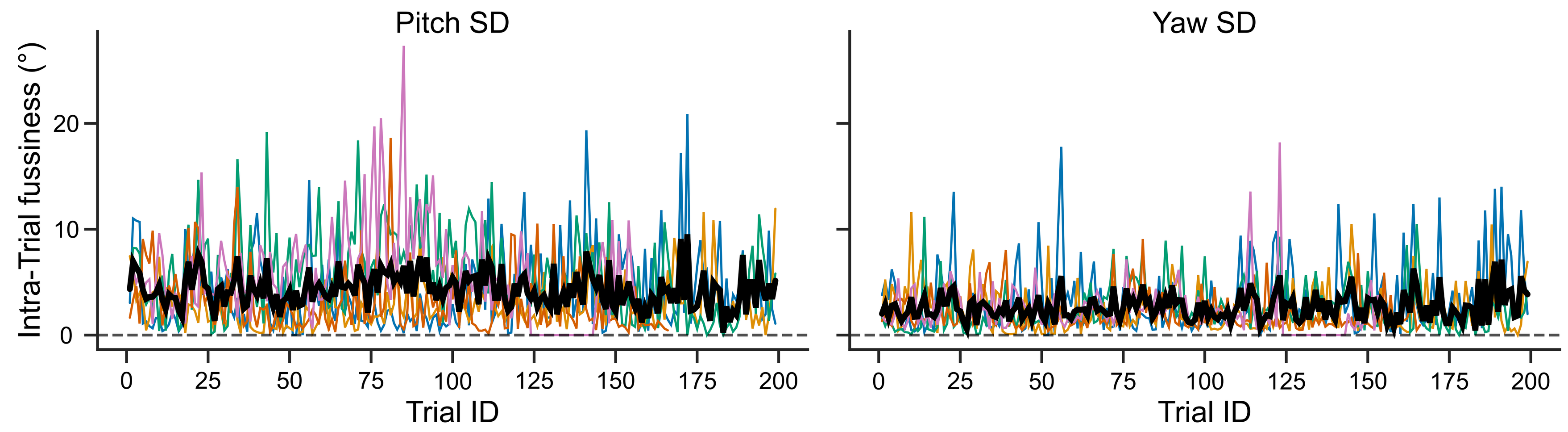


Fig. 6: Intra-trial head pose variability (fussiness). Variability shown here is defined as one standard deviation away from the subject mean. Each colored line represents one subject.

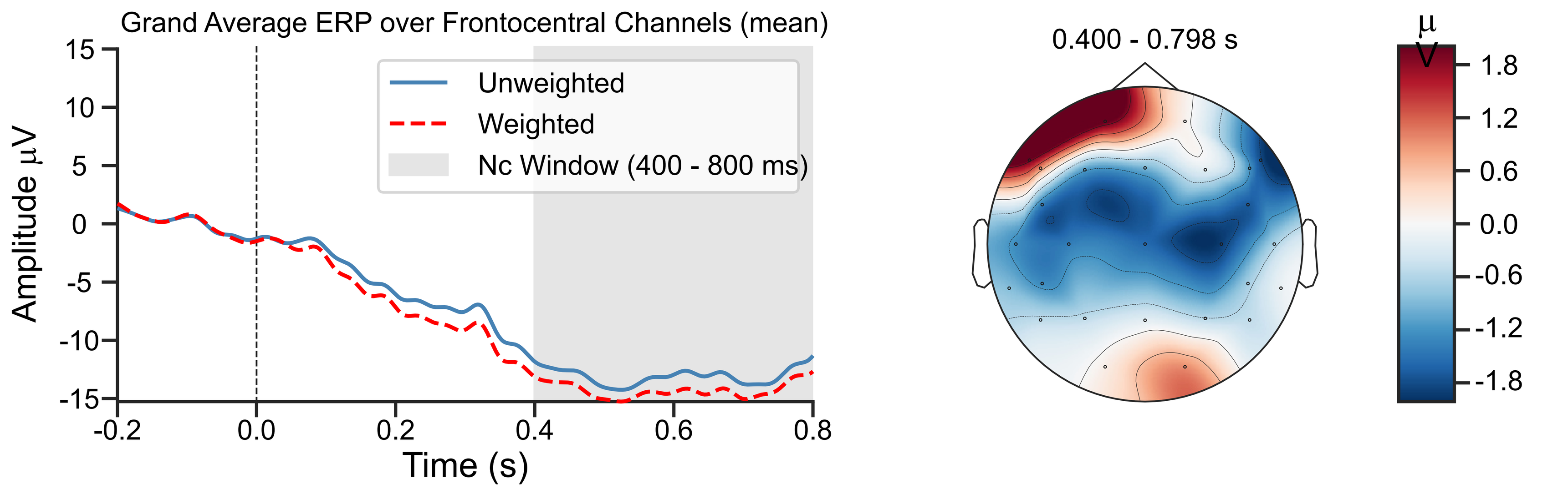


Fig. 9: Comparison of Central Negativity (Nc) grand average between unweighted versus weighted trial data. The waveform is computed as the average over frontocentral channels F3, F4, Fz, C3, C4, Cz for five infants and 3 sessions, respectively. Weights are estimated as trial-averaged absolute head pose deviation away from baseline, normalized between 0 and 1. High head pose deviation values are assumed to relate to decreased attention, and are thus assigned a lower weight. Low head pose deviation values are assumed to relate to increased attention, and are thus assigned a higher weight. The red curve represents the product of the weighted trials, whereas the blue line represents the unweighted trials.

Conclusion

With **minimal extra effort** during data collection and processing, **OCAPI** provides an easy way to **extract additional behavioral information** that meaningfully improves our understanding of infant populations in a lab setting, making tailored adjustments to the lab setup easier. It also boosts productivity and data quality by automating the otherwise labor-intensive coding of infant behavior.

The method is **objective, deterministic, and transparently reportable**—qualities that align well with open science practices.

Parameters can be adjusted as needed, allowing researchers to **accommodate individual study goals**.

Gaining structured insights into infant movement during experiments—and obtaining a clearer, operational measure of the previously vague concept of "**fussiness**"—offers substantial benefits for researchers across many areas of infant science.

Open Questions

- What is needed to consider **implementation** in your own research?
- What **functionalities** are unclear?
- What would you like to see to "trust" OCAPI with your data?
- Which functionalities would you additionally need for your own research?
- What data output would be desirable?

References

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